Credit Risk Modelling For Dummies: But With Fewer Dummies

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Overview

Standard credit risk analysis utilises scorecards which are built using only datasets with categorical variables. This requires the continuous numerical features to be fine-classed (grouped into discrete sets) and converted to dummy variables. Although the point of the scorecard is to present the model in a simple way, this practice requires much convoluted pre-processing of the data, which greatly bloats the size of the dataset and makes it more susceptible to containing errors. Most importantly though, I find that, by retaining the numerical features, the predictive power of the data is great improved, with a Gini coefficient of 0.98 (cf. 0.40 with fine-classing) and Kolmogorov-Smirnov statistic of $KS = 0.97$ (cf. 0.30).

Contents

1 Introduction

Credit risk addresses the potential loss a lender or investor may face if a borrower or debtor fails to repay a loan or meet their financial obligations. It is a critical consideration for financial institutions, as a high level of credit risk can lead to significant financial losses and even bankruptcy. Accurately assessing credit risk is essential for lenders to make informed decisions about whether to extend credit and the terms of the loan.

Coarse and fine classing are methods used to assess credit risk. *Coarse classing* involves grouping borrowers or debtors into broad categories based on their creditworthiness, such as high, medium, or low risk. *Fine classing*, on the other hand, involves a more detailed analysis of credit risk, using a more nuanced approach to identify different levels of creditworthiness within each broad category.

Classing is used as credit regulators require statistical models for estimating credit risk to be presented in a simple way (the scorecard). This is based upon the coefficients in the *probability of default* model and must only contain only dummy variables as predictive features. However, fine classing (which generates typically 20 – 50 features) can lead quickly to a very bloated dataset. This requires more processing memory and is effectively an unnecessary degradation of any continuous (non-discrete data), while making the pre-processing of data more complex and thus more prone to errors.

Here I demonstrate that not fine classing can deliver a significantly greater predictive power[1], while simplifying the pre-processing of the data.

2 Pre-processing

2.1 Initial pre-processing

2.1.1 The data

The dataset `loan_data_200_2014.csv` (available from Kaggle) contains all available data for more than 800 000 consumer loans issued from 2007 to 2015 by LendingClub, a large U.S. peer to peer lending company.

Running `pre-process_1.py`, it is seen that there are `466285 rows x 75 columns`. Also, it is evident that there are a lot of missing values (`NaN`) and a lot of feature columns which are completely empty, e.g.

```
54  annual_inc_joint              0 non-null        float64
55  dti_joint                     0 non-null        float64
56  verification_status_joint     0 non-null        float64
```

To start with, I drop the features with $> 200\,000$ missing values (a large fraction of the data). These are

```
desc has 340302 missing values
```

[1]Compared to Udemy's Credit Risk Modelling in Python and Credit Risk Modelling (Part II).

```
mths_since_last_delinq has 250351 missing values
mths_since_last_record has 403647 missing values
next_pymnt_d has 227214 missing values
mths_since_last_major_derog has 367311 missing values
annual_inc_joint has 466285 missing values
dti_joint has 466285 missing values
verification_status_joint has 466285 missing values
open_acc_6m has 466285 missing values
open_il_6m has 466285 missing values
open_il_12m has 466285 missing values
open_il_24m has 466285 missing values
mths_since_rcnt_il has 466285 missing values
total_bal_il has 466285 missing values
il_util has 466285 missing values
open_rv_12m has 466285 missing values
open_rv_24m has 466285 missing values
max_bal_bc has 466285 missing values
all_util has 466285 missing values
inq_fi has 466285 missing values
total_cu_tl has 466285 missing values
inq_last_12m has 466285 missing values
```

The extraneous fields – `Unnamed: 0` and `member_id` are also removed. At this stage, `id` (a unique ID for the loan) is retained as this will be useful in recombining the data if this is split (e.g. Sect. 2.1.4). After removal there are 50 feature columns remaining.

2.1.2 Times and dates

Following the Udemy analysis, the next step is to covert the *employment length* (`emp_length`) and *term of the loan* (`term`) to numeric values. That is

```
['10+ years' '< 1 year' '1 year' '3 years' '8 years' '9 years' '4 years'
 '5 years' '6 years' '2 years' '7 years' nan]

[' 36 months' ' 60 months']
```

which become

```
['10' '0' '1' '3' '8' '9' '4' '5' '6' '2' '7' nan]
[36 60]
```

In order to limit empty space between the columns when viewing the data-frame, I have also shortened the feature name `emp_length` to `EM_L`.

The *earliest credit line* (`earliest_cr_line_date`) field also has to be converted into a useful format, and using

```
pd.to_datetime(df['earliest_cr_line'],
               format = '%b-%y')
```

gives the second column to the right from the original first. I also shorten `earliest_cr_line_date` to ECL.

```
0       Jan-85      0       1985-01-01
1       Apr-99      1       1999-04-01
2       Nov-01      2       2001-11-01
3       Feb-96      3       1996-02-01
4       Jan-96      4       1996-01-01
          ...                   ...
466280  Apr-03      466280  2003-04-01
466281  Jun-97      466281  1997-06-01
466282  Dec-01      466282  2001-12-01
466283  Feb-03      466283  2003-02-01
466284  Feb-00      466284  2000-02-01
```

However, looking at the converted dates, the latest is over 40 years in the future! While this suggests super predictive power it is probably inadvisable to rely on this. As the Udemy course suggests, this is due to the built-in time scale starting from 1970 (it actually looks like the start of 1969).

```
count                  466256
unique                    664
top       2000-10-01 00:00:00
freq                     3674
first     1969-01-01 00:00:00
last      2068-12-01 00:00:00
Name: ECL, dtype: object
```

Looking at the latest `earliest_cr_line_date` (ECL) before today

```
from datetime import date
today = np.datetime64(date.today()); print(today)
temp = df[df['ECL'] < today]; print(temp['ECL'].describe())
```

gives `2011-11-01` as the latest ECL date.

The earliest credit line is then converted to months since this date (Udemy uses December 2017), giving the output to the right. The error in the dates seen above is apparent from the minimum number of months since the earliest credit line.

```
count    466256.000000
mean        166.492177
std          93.976747
min        -685.024333
max         513.981807
```

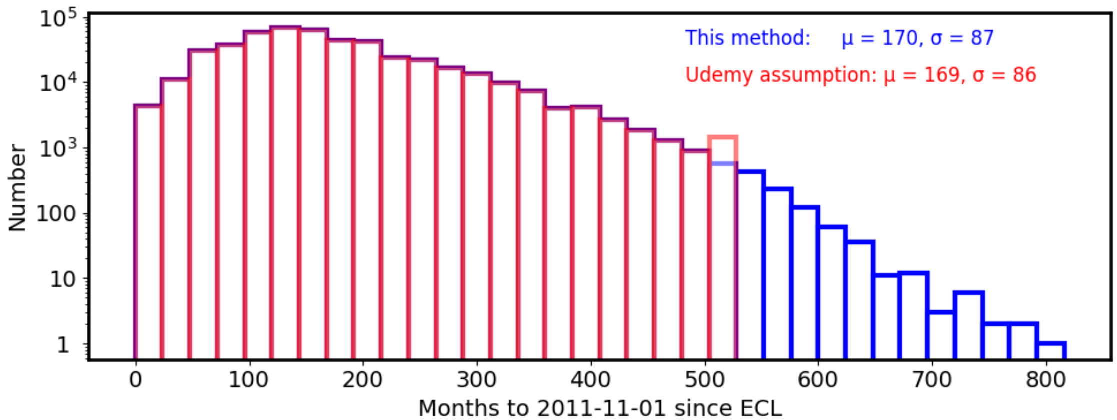
The Udemy course deals with this by substituting the negative values for the maximum observed positive difference, with the justification "*Even if we don't calculate the exact number of months that have passed since the earliest credit line was issued for those issued in the 60s, we put a very large value and we still get pretty close to the real picture.*"

However, it is arguable whether these values are *very large*, as well as the potential of unnecessarily losing crucial information. By splitting the date string and subtracting 100 from the year for which the number of months are negative, we can obtain the correct number of months since the earliest credit line.

```
count    466256.000000        count    466256.000000
mean        169.395094        mean        169.500887
std          86.461715        std          86.930703
```

```
min        0.000000       min        0.000000
max      513.981807       max      814.012608
```

From the mean values and the plot below, it is seem that the Udemy assumption should have minimum impact, although this could be an issue if working with a significant fraction of older (pre-1970) loans. So while the assumption is easier to implement, it may not always be warranted.



This procedure is repeated to get the months since the loan issue date (issue_d). This spans 2007-06-01 to 2014-12-01 and so no conversion of pre-1970 dates is required. This is also the case for last_pymnt_d (2007-12-01 to 2016-01-01) and last_credit_pull_d (2007-12-01 to 2016-01-01), which are also converted.

```
count                   466256
unique                      91
top        2014-10-01 00:00:00
freq                     38782
first      2007-06-01 00:00:00
last       2014-12-01 00:00:00
Name: i_date, dtype: object
```

2.1.3 Further trimming

Before dealing with the categorical features, the data which appear to be of limited value are further trimmed:

- url – as these are unique to each customer[2]
- zip_code – which are only partial (e.g. 860xx) and we will use the *address state* (addr_state)
- sub_grade – as credit worthiness grade (grade) will be used, and perhaps coarse classed (Sect. 2.2.1) so that higher resolution values will not be needed
- application_type – which only has a single value (namely INDIVIDUAL)

Revisiting the missing values

[2] Of the form https://www.lendingclub.com/browse/loanDetail.action?loan_id= ...

```
emp_title has 27541 missing values
title has 20 missing values
revol_util has 305 missing values
collections_12_mths_ex_med has 115 missing values
tot_coll_amt has 70130 missing values
tot_cur_bal has 70130 missing values
total_rev_hi_lim has 70130 missing values
EM_L has 20983 missing values
```

the employment length (EM_L) could be important, as well as the borrower's job title (emp_title), so I initially removed only those with $> 30\,000$ missing values. Of the remaining missing values:

- emp_title has 205 271 unique values, but these are categorical, which would require too many dummy variables, so this is *removed*.
- title has 63015 unique values which are also categorical, so this is *removed*.
- revol_util has 1270 unique values which are numerical, so this will be *imputed*.
- collections_12_mths_ex_med has 10 unique values which are numerical, so this will be *imputed*.
- EM_L has 12 unique values which are numerical, so this will be *imputed*.

Which now leaves 41 features in the data.

2.1.4 Imputing the remaining missing values

There are various methods available to impute missing data, with the most common being *simple imputation*, where the missing feature is replaced with either a constant, the mean, the median or the most frequently occurring value. Since this is basically just using an assumed value, I opted for *multivariate (multiple) imputation*, where machine learning is used to estimate the missing values from the other features.

Bearing in mind the caveats that the employment length EM_L contains both lower (10+ years) and upper limits (< 1 year), I summarise the effects of the imputation below.

```
------------ BEFORE IMPUTATION --------------
For revol_util, n = 465534, mean = 56.181 +/- 23.730
For collections_12_mths_ex_med, n = 465724, mean = 0.009 +/- 0.109
For EM_L, n = 444856, mean = 5.994 +/- 3.627


------------ AFTER IMPUTATION --------------
For revol_util, n = 465839, mean = 56.186 +/- 23.725
For collections_12_mths_ex_med, n = 465839, mean = 0.009 +/- 0.109
For EM_L, n = 465839, mean = 6.019 +/- 3.555
```

2.1.5 Formatting the target variable

The target variable is the `loan_status`, which has the unique values

```
'Fully Paid'           'Late (31-120 days)'
'Charged Off'          'In Grace Period'
'Late (16-30 days)'    'Does not meet the credit policy. Status:Fully Paid'
'Current'              'Does not meet the credit policy. Status:Charged Off'
'Default'
```

of which, e.g. `Fully Paid`, `Current` and `In Grace Period` are considered good loans and `Charged Off` and `Default` as bad.

In order to classify these, I calculate the *debt-to-income ratio* (DTIR) for each category.[3] To get the debt, I subtracted the *principal received to date* (`total_rec_prncp`) from the *loan amount* (`loan_amnt`). In increasing debt-to-income ratio, the results are

	loan_status	number	mean DTIR	standard error
0	Fully Paid	184724	0.0008	0.0
7	Does not meet the credit policy. Status:Fully ...	1961	0.0027	0.0004
8	Does not meet the credit policy. Status:Charge...	746	0.1194	0.0036
2	Current	224207	0.1283	0.0002
5	In Grace Period	3146	0.1399	0.0016
6	Late (16-30 days)	1218	0.1411	0.0026
4	Late (31-120 days)	6900	0.1587	0.0011
3	Default	832	0.1743	0.0034
1	Charged Off	42105	0.1833	0.0005

I flagged all statuses above `Late (16-30 days)`, or DTIR $\lesssim 0.15$, as good/non-defaulted (`good` $= 1$) and those below, or DTIR $\gtrsim 0.15$, as bad/defaulted (`good = 0`) loans.
This results in 416 002 `good` $= 1$ loans and and 49837 `good = 0`, which differ slightly from the Udemy numbers (see Sect. 4.4), which are from an unspecified regression model.

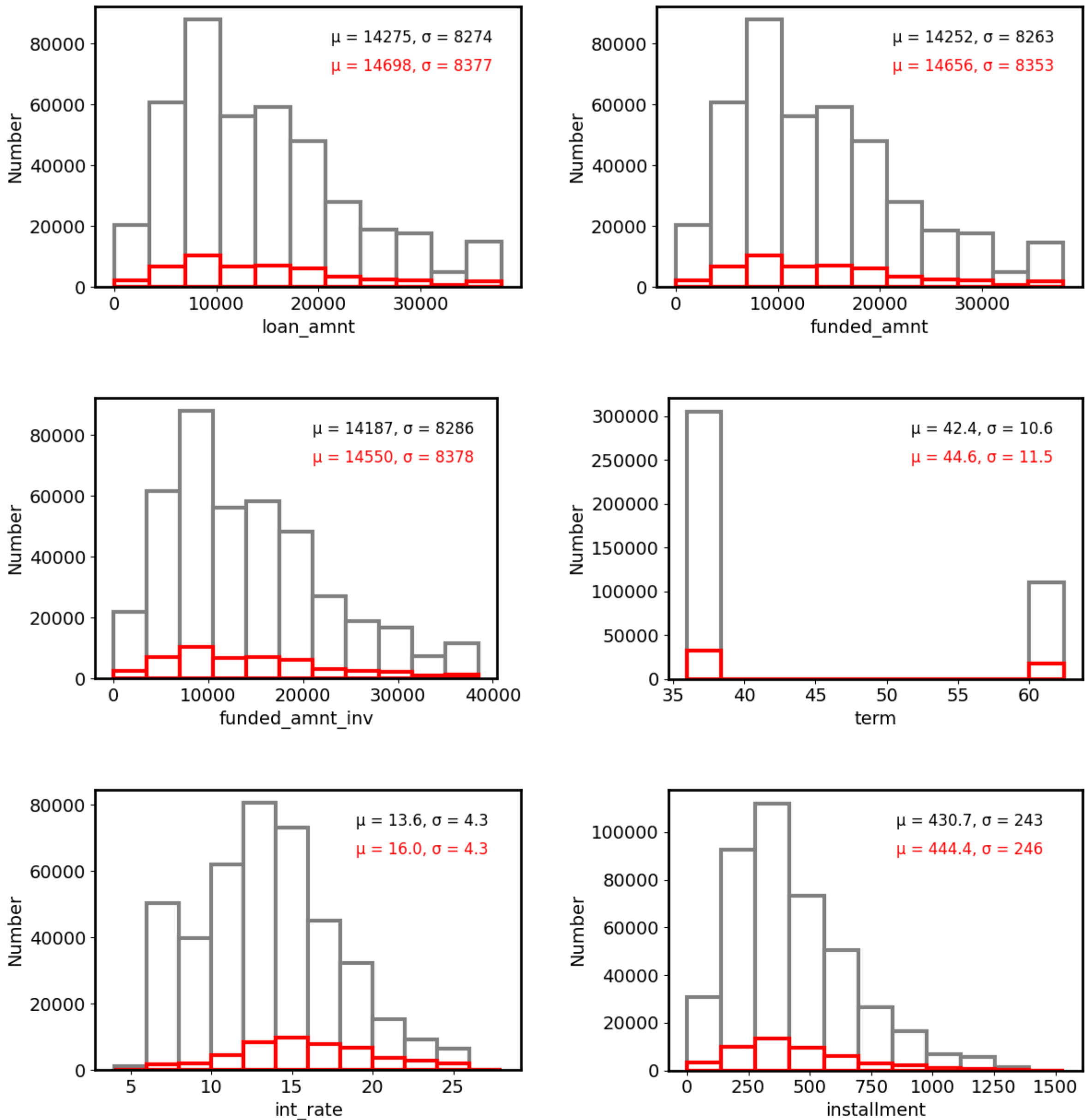
	loan_status	good
0	Fully Paid	1
1	Charged Off	0
2	Fully Paid	1
...	...	...
465836	Current	1
465837	Fully Paid	1
465838	Current	1

Since this completes the first phase of the pre-processing and the code is becoming cumbersome, the currently processed data are saved to `loan_data_2007_2014_1.csv`.

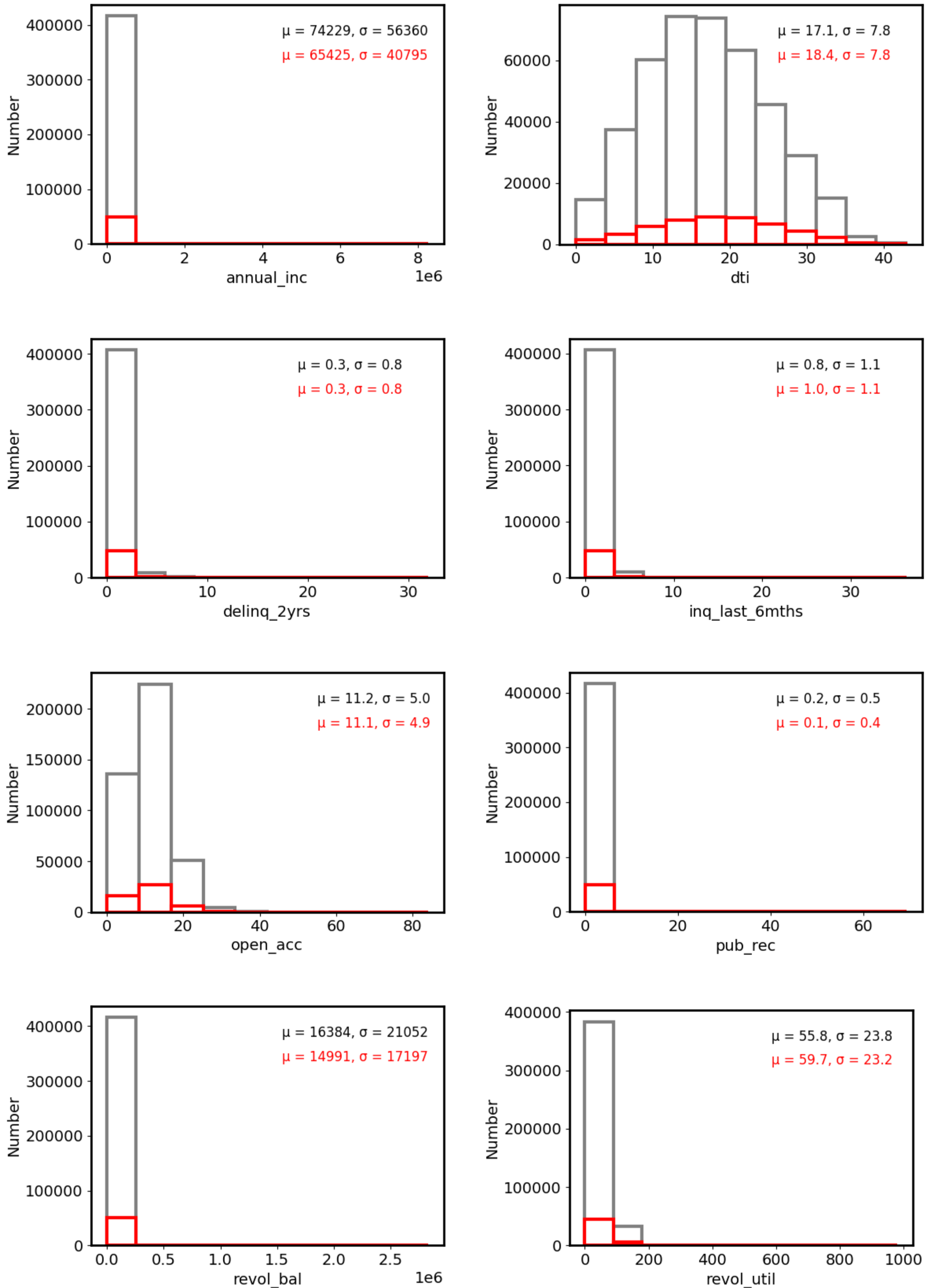
This file is read into `feature_histos.py` to show the distributions for each of the numeric features according to good (black) and bad (red histogram) loans. From these, the good and bad loans mostly overlap, although

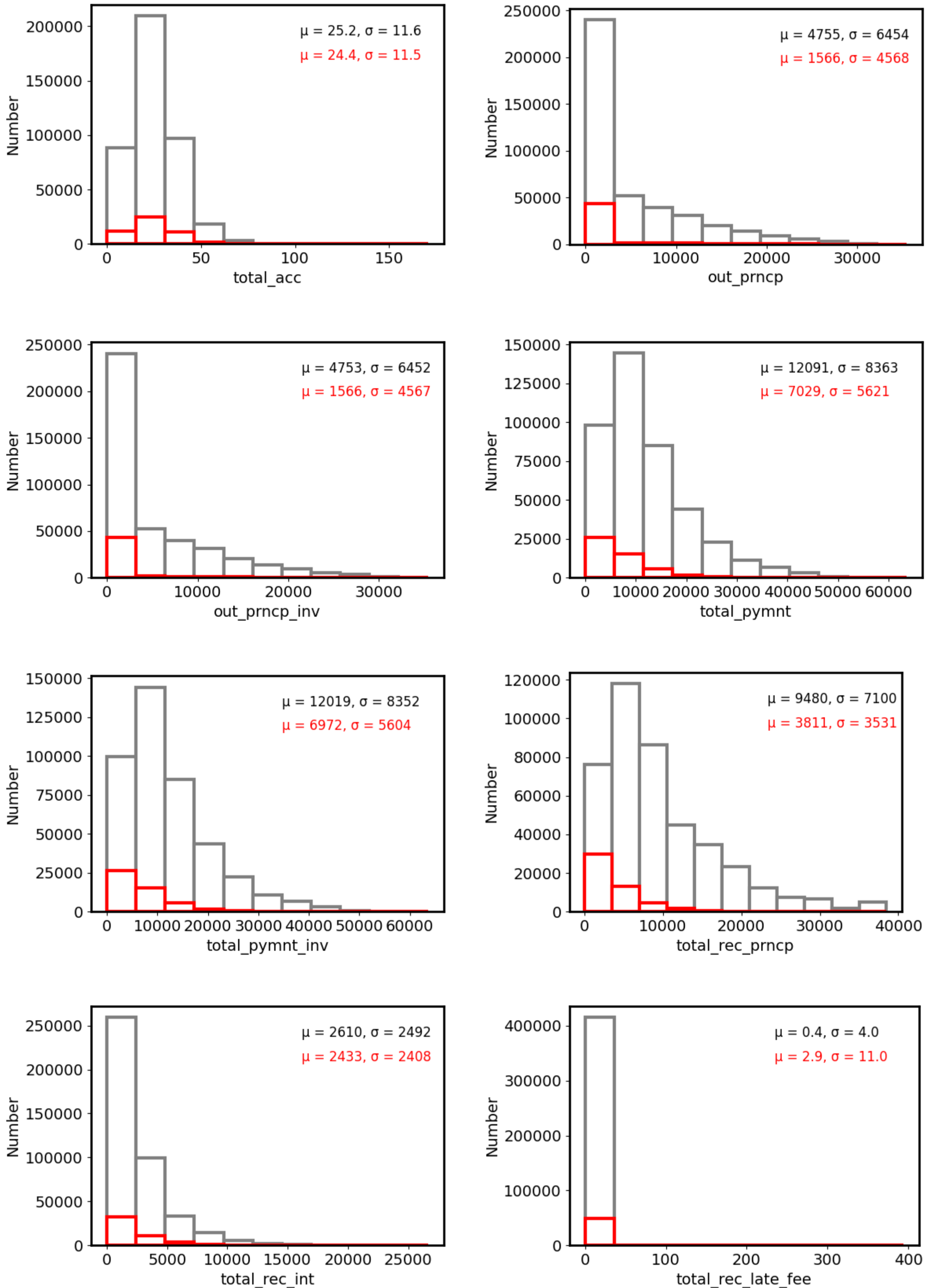
[3] Note that the feature `dti` is not the debt-to-income ratio, but, according to Kaggle, a ratio of the borrower's total monthly debt payments on the total debt obligation.

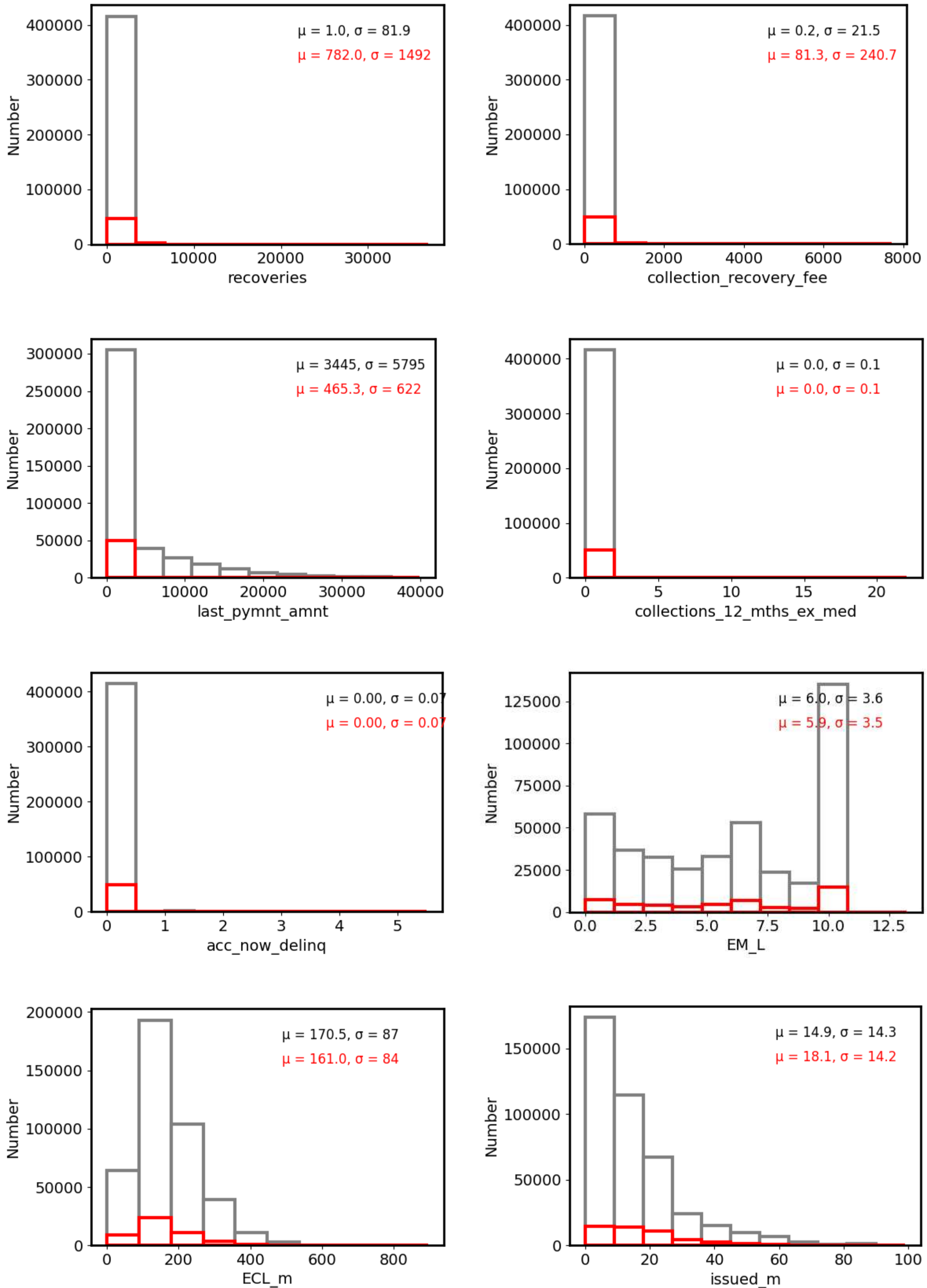
recoveries, collection_recovery_fee, LP_m, debt and, not surprisingly[4], DTIR appear distinctive, the standard deviations in the data are very wide. This demonstrates that bad loans would be difficult to distinguish based upon the distributions alone.

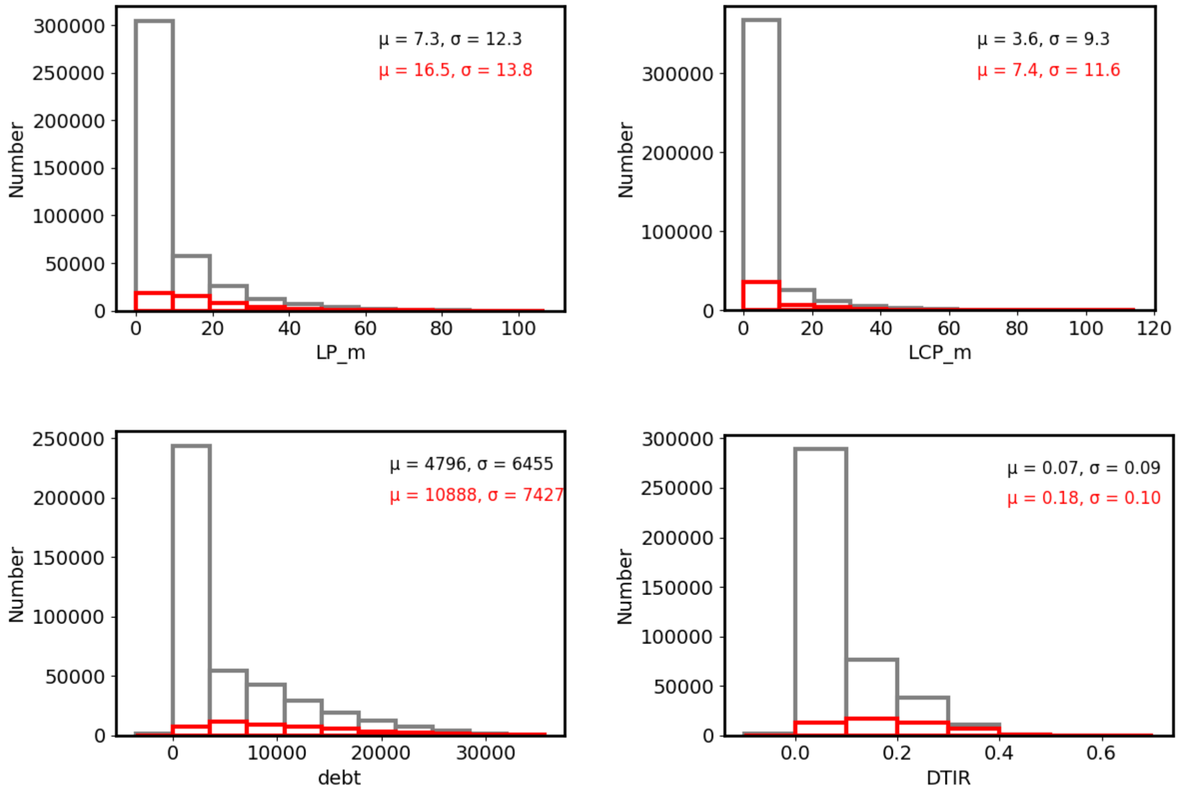


[4]Since this was used to classify the loan as being good or bad.


μ = 74229, σ = 56360
μ = 65425, σ = 40795
Number
annual_inc
1e6
μ = 17.1, σ = 7.8
μ = 18.4, σ = 7.8
dti
μ = 0.3, σ = 0.8
μ = 0.3, σ = 0.8
delinq_2yrs
μ = 0.8, σ = 1.1
μ = 1.0, σ = 1.1
inq_last_6mths
μ = 11.2, σ = 5.0
μ = 11.1, σ = 4.9
open_acc
μ = 0.2, σ = 0.5
μ = 0.1, σ = 0.4
pub_rec
μ = 16384, σ = 21052
μ = 14991, σ = 17197
revol_bal
μ = 55.8, σ = 23.8
μ = 59.7, σ = 23.2
revol_util


μ = 25.2, σ = 11.6
μ = 24.4, σ = 11.5
Number
total_acc
μ = 4755, σ = 6454
μ = 1566, σ = 4568
Number
out_prncp
μ = 4753, σ = 6452
μ = 1566, σ = 4567
Number
out_prncp_inv
μ = 12091, σ = 8363
μ = 7029, σ = 5621
Number
total_pymnt
μ = 12019, σ = 8352
μ = 6972, σ = 5604
Number
total_pymnt_inv
μ = 9480, σ = 7100
μ = 3811, σ = 3531
Number
total_rec_prncp
μ = 2610, σ = 2492
μ = 2433, σ = 2408
Number
total_rec_int
μ = 0.4, σ = 4.0
μ = 2.9, σ = 11.0
Number
total_rec_late_fee


μ = 1.0, σ = 81.9
μ = 782.0, σ = 1492
Number
recoveries
μ = 0.2, σ = 21.5
μ = 81.3, σ = 240.7
Number
collection_recovery_fee
μ = 3445, σ = 5795
μ = 465.3, σ = 622
Number
last_pymnt_amnt
μ = 0.0, σ = 0.1
μ = 0.0, σ = 0.1
Number
collections_12_mths_ex_med
μ = 0.00, σ = 0.07
μ = 0.00, σ = 0.07
Number
acc_now_delinq
μ = 6.0, σ = 3.6
μ = 5.9, σ = 3.5
Number
EM_L
μ = 170.5, σ = 87
μ = 161.0, σ = 84
Number
ECL_m
μ = 14.9, σ = 14.3
μ = 18.1, σ = 14.2
Number
issued_m



2.2 Coarse classing of categorical values

Although, unlike the standard practice (e.g. Udemy), I will not convert the continuous variables to dummy variables, this should be done for the categorical values in order to fully utilise the available data. I will then assess the feature's explanatory power (information value) with respect to the borrower classification.

The remaining categorical fields are

```
['grade', 'home_ownership', 'verification_status', 'pymnt_plan', 'purpose',
     'addr_state', 'initial_list_status'],
```

which are worked through one-by-one in `pre-process_2.py`, below.

2.2.1 Grade

The `grade` feature, which represents an external grade showing the credit worthiness of the borrower, ranging from A (the highest) to G (the lowest), has only seven unique values.

Here and for the following categories, as per the standard practice, we wish to know how relevant the feature is to the target variable. For this the *weight of evidence* for each value of the feature is used,

$$WoE_i \equiv \ln\left(\frac{\%(y=1)_i}{\%(y=0)_i}\right) = \ln\left(\frac{\%\ \text{good}_i}{\%\ \text{bad}_i}\right),$$

which is the natural logarithm of the ratio of proportion of observations in the first target category to those in the second.

Multiplying the *WoE* by the difference in the proportions and summing, gives the *information value*

$$IV = \sum_{i=1}^{k}\left[(\%\text{good} - \%\text{bad}) \times \ln\left(\frac{\%\ \text{good}}{\%\ \text{bad}}\right)\right],$$

which quantifies how much information the feature contributes to explaining the target. The information value ranges from $IV = 0$ to 1 according to its predictive power (summarised in the table).

Information value	**Predictive power**
$IV < 0.02$	None
$0.02 < IV < 0.1$	Weak
$0.1 < IV < 0.3$	Medium
$0.3 < IV < 0.5$	Strong
$IV > 0.5$	Suspect

Proceeding with the grade feature, in increasing *WoE*

```
n_obs   - number of observations for this grade
%n_obs  - perentage of total number of observations
n_good  - number of good = 1 observations for this grade (bad loans are flagged 'good = 0')
%good   - percentage of good = 1 observations for this grade
%n_good - perentage of total number

  grade   n_obs  %n_obs  n_good  n_bad  %good   %bad  %n_good  %n_bad   WoE        IV
0     G    3316    0.71    2470    846  74.49  25.51     0.59    1.70 -1.06  0.011766
1     F   13205    2.83   10129   3076  76.71  23.29     2.43    6.17 -0.93  0.034782
2     E   35679    7.66   28945   6734  81.13  18.87     6.96   13.51 -0.66  0.043230
3     D   76784   16.48   65228  11556  84.95  15.05    15.68   23.19 -0.39  0.029289
4     C  125186   26.87  111042  14144  88.70  11.30    26.69   28.38 -0.06  0.001014
5     B  136848   29.38  126233  10615  92.24   7.76    30.34   21.30  0.35  0.031640
6     A   74821   16.06   71955   2866  96.17   3.83    17.30    5.75  1.10  0.127050
==============================================================================================
For 'grade' feature, sum of IVs = 0.2788: 0.1 < IV < 0.3 - medium predictive power
==============================================================================================
```

The predictive power of the grade feature is close to the medium/strong threshold.

Since there are only seven different values, each with a large number of observations, the dummy variables can be one-hot-encoded directly, thus not requiring coarse classing, giving, for example,

```
         good  grade_A  grade_B  grade_C  grade_D  grade_E  grade_F  grade_G
0           1        0        1        0        0        0        0        0
1           0        0        0        1        0        0        0        0
```

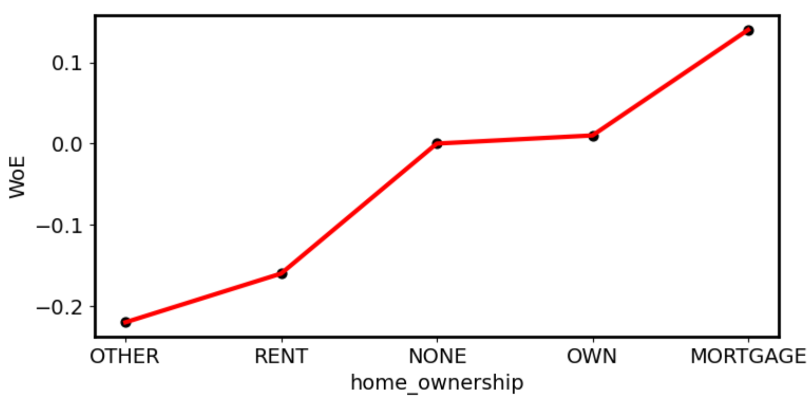
```
2           1      0      0      1      0      0      0      0
...         ...    ...    ...    ...    ...    ...    ...    ...
465837      1      1      0      0      0      0      0      0
465838      1      0      0      0      1      0      0      0
```

2.2.2 Home ownership

Since the *WoE* and *IV* calculations are in a function (in `pre-process_2.py`), it is trivial to get these metrics for the remaining features. Continuing with `home_ownership`

	home_ownership	n_obs	%n_obs	n_good	n_bad	%good	%bad	%n_good	%n_bad	WoE	IV
0	OTHER	182	0.04	155	27	85.16	14.84	0.04	0.05	-0.22	0.000022
1	RENT	188208	40.40	165019	23189	87.68	12.32	39.67	46.53	-0.16	0.010976
2	NONE	46	0.01	39	7	84.78	15.22	0.01	0.01	0.00	0.000000
3	OWN	41654	8.94	37231	4423	89.38	10.62	8.95	8.87	0.01	0.000008
4	MORTGAGE	235748	50.61	213557	22191	90.59	9.41	51.34	44.53	0.14	0.009534
5	ANY	1	0.00	1	0	100.00	0.00	0.00	0.00	NaN	NaN

```
==========================================================================================
For 'home_ownership' feature, sum of IVs = 0.0205: 0.02 < IV < 0.1 - weak predictive power
==========================================================================================
```



If using this feature, given the low IV, the small numbers (`n_obs`) for `OTHER`, `NONE` and `ANY` means that it is not sensible to one-hot-encode these. Therefore, `OTHER` is merged with the nearest populous value with a similar *WoE*, `RENT`. Likewise, `NONE` and `ANY` is merged with `OWN`.

After merging (and renaming for neatness), we are left with the fields `HO_MORTGAGE HO_RENT+ HO_OWN+`, where the '+' designates the inclusion of other groups.

2.2.3 Verification status

There is no information regarding the `verification_status` on either Udemy's Credit Risk Modelling in Python nor Kaggle.

Running the `woe` function in `pre-process_2.py`,shows that there are only three unique values, each of which has a large, and similar, number of observations.

	VS	n_obs	%n_obs	n_good	n_bad	%good	%bad	%n_good	%n_bad	WoE	IV
0	Verified	167920	36.05	146802	21118	87.42	12.58	35.29	42.37	-0.18	0.012744
1	Source Verified	149862	32.17	134444	15418	89.71	10.29	32.32	30.94	0.04	0.000552
2	Not Verified	148057	31.78	134756	13301	91.02	8.98	32.39	26.69	0.19	0.010830

```
==========================================================================================
For 'VS' feature, sum of IVs = 0.0241: 0.02 < IV < 0.1 - weak predictive power
==========================================================================================
```

Therefore, there is no need to coarse class this feature, which are therefore converted to dummy variables directly.

2.2.4 Payment plan

This flags whether a payment plan has been put in place for the loan.

	PP	n_obs	%n_obs	n_good	n_bad	%good	%bad	%n_good	%n_bad	WoE	IV
0	y	9	0.0	5	4	55.56	44.44	0.0	0.01	-inf	inf
1	n	465830	100.0	415997	49833	89.30	10.70	100.0	99.99	0.0	0.0

```
==========================================================================================
For 'PP' feature, sum of IVs = inf: IV >  0.5 - something fishy going on
==========================================================================================
```

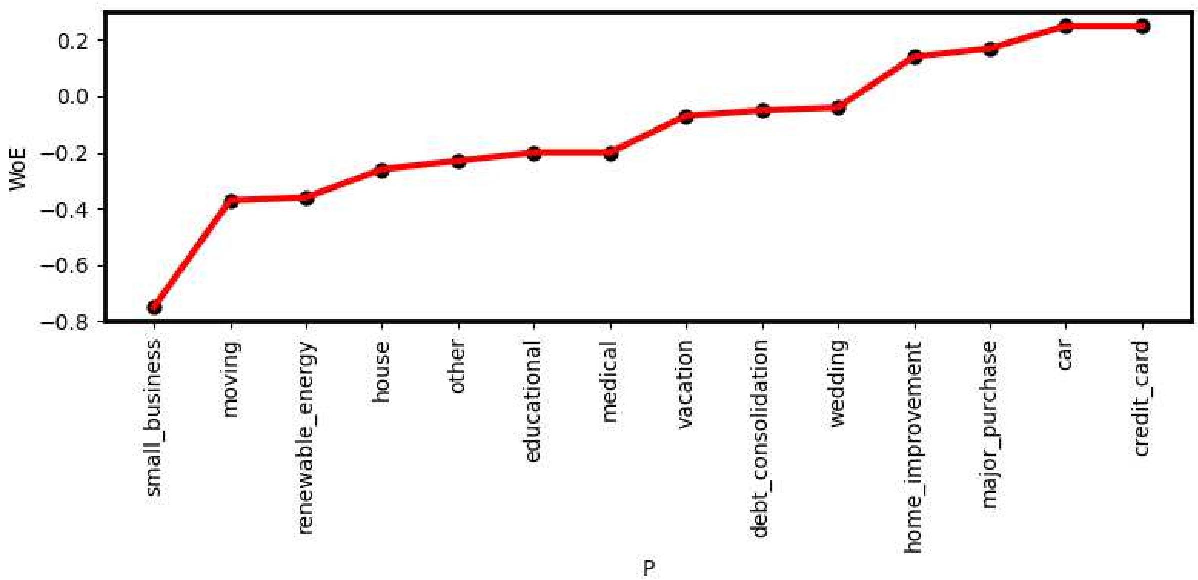
There are just two values, with the number of `PP = y` being so small that the feature is almost exclusively `PP = n`. This highly unbalanced feature is therefore removed.

2.2.5 Purpose

This is the purpose of the loan.

P	n_obs	%n_obs	n_good	n_bad	%good	%bad	%n_good	%n_bad	WoE	IV
small_business	6993	1.50	5572	1421	79.68	20.32	1.34	2.85	-0.75	0.011325
moving	2990	0.64	2551	439	85.32	14.68	0.61	0.88	-0.37	0.000999
renewable_energy	349	0.07	298	51	85.39	14.61	0.07	0.10	-0.36	0.000108
house	2264	0.49	1962	302	86.66	13.34	0.47	0.61	-0.26	0.000364
other	23607	5.07	20507	3100	86.87	13.13	4.93	6.22	-0.23	0.002967
educational	419	0.09	366	53	87.35	12.65	0.09	0.11	-0.20	0.000040
medical	4588	0.98	4007	581	87.34	12.66	0.96	1.17	-0.20	0.000420
vacation	2484	0.53	2200	284	88.57	11.43	0.53	0.57	-0.07	0.000028
debt_consolidation	273984	58.82	243389	30595	88.83	11.17	58.51	61.39	-0.05	0.001440
wedding	2331	0.50	2071	260	88.85	11.15	0.50	0.52	-0.04	0.000008
home_improvement	26510	5.69	24001	2509	90.54	9.46	5.77	5.03	0.14	0.001036
major_purchase	9813	2.11	8911	902	90.81	9.19	2.14	1.81	0.17	0.000561
car	5389	1.16	4929	460	91.46	8.54	1.18	0.92	0.25	0.000650

```
      credit_card  104118  22.35  95238  8880  91.47   8.53  22.89 17.82  0.25  0.012675
===============================================================================================
For 'P' feature, sum of IVs = 0.0326: 0.02 < IV < 0.1 - weak predictive power
===============================================================================================
```



There are some low numbers of observations (e.g. `renewable_energy`), which could be merged with the other values (as in Sect. 2.2.2), but given that there are 14 unique values, these should be bundled into coarser classes in any case.

With the guidance of the *WoE* values in the above table and the plot, the dummies are combined as

```
comb_dummy('P',['small_business', 'moving','renewable_energy'])
comb_dummy('P',['other','house','educational','medical'])
comb_dummy('P',['debt_consolidation','vacation','wedding'])
comb_dummy('P',['home_improvement','major_purchase'])
comb_dummy('P',['credit_card','car']);
```

leaving the features

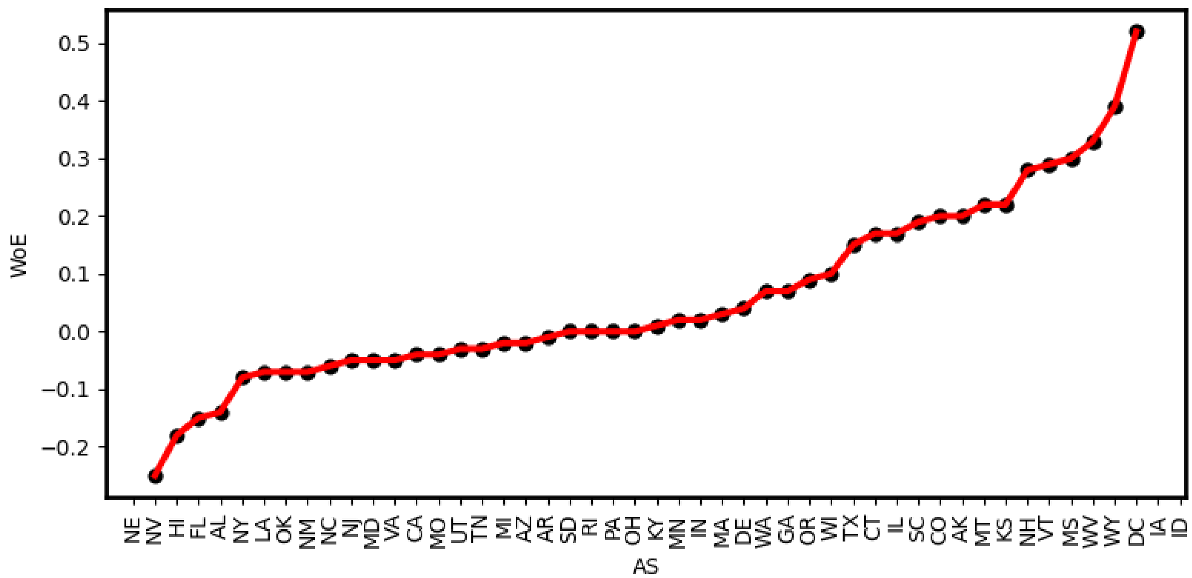
```
P_small_business+  P_other+  P_debt_consolidation+  P_home_improvement+  P_credit_card+
```

2.2.6 Address state

	AS	n_obs	%n_obs	n_good	n_bad	%good	%bad	%n_good	%n_bad	WoE	IV
0	NE	14	0.00	9	5	64.29	35.71	0.00	0.01	-inf	inf
1	NV	6508	1.40	5641	867	86.68	13.32	1.36	1.74	-0.25	0.000950
2	HI	2485	0.53	2175	310	87.53	12.47	0.52	0.62	-0.18	0.000180

3	FL	31609	6.79	27738	3871	87.75	12.25	6.67	7.77	-0.15	0.001650
4	AL	5849	1.26	5138	711	87.84	12.16	1.24	1.43	-0.14	0.000266
5	NY	40189	8.63	35585	4604	88.54	11.46	8.55	9.24	-0.08	0.000552
6	LA	5483	1.18	4853	630	88.51	11.49	1.17	1.26	-0.07	0.000063
7	OK	4111	0.88	3644	467	88.64	11.36	0.88	0.94	-0.07	0.000042
8	NM	2586	0.56	2292	294	88.63	11.37	0.55	0.59	-0.07	0.000028
9	NC	12669	2.72	11233	1436	88.67	11.33	2.70	2.88	-0.06	0.000108
10	NJ	18039	3.87	16018	2021	88.80	11.20	3.85	4.06	-0.05	0.000105
11	MD	10959	2.35	9735	1224	88.83	11.17	2.34	2.46	-0.05	0.000060
12	VA	14211	3.05	12616	1595	88.78	11.22	3.03	3.20	-0.05	0.000085
13	CA	71369	15.32	63425	7944	88.87	11.13	15.25	15.94	-0.04	0.000276
14	MO	7500	1.61	6669	831	88.92	11.08	1.60	1.67	-0.04	0.000028
15	UT	3428	0.74	3052	376	89.03	10.97	0.73	0.75	-0.03	0.000006
16	TN	5980	1.28	5323	657	89.01	10.99	1.28	1.32	-0.03	0.000012
17	MI	11542	2.48	10283	1259	89.09	10.91	2.47	2.53	-0.02	0.000012
18	AZ	10702	2.30	9534	1168	89.09	10.91	2.29	2.34	-0.02	0.000010
19	AR	3488	0.75	3108	380	89.11	10.89	0.75	0.76	-0.01	0.000001
20	SD	980	0.21	876	104	89.39	10.61	0.21	0.21	0.00	0.000000
21	RI	2049	0.44	1828	221	89.21	10.79	0.44	0.44	0.00	0.000000
22	PA	16416	3.52	14660	1756	89.30	10.70	3.52	3.52	0.00	0.000000
23	OH	15228	3.27	13605	1623	89.34	10.66	3.27	3.26	0.00	0.000000
24	KY	4433	0.95	3967	466	89.49	10.51	0.95	0.94	0.01	0.000001
25	MN	8150	1.75	7292	858	89.47	10.53	1.75	1.72	0.02	0.000006
26	IN	6523	1.40	5841	682	89.54	10.46	1.40	1.37	0.02	0.000006
27	MA	11058	2.37	9913	1145	89.65	10.35	2.38	2.30	0.03	0.000024
28	DE	1270	0.27	1139	131	89.69	10.31	0.27	0.26	0.04	0.000004
29	WA	10508	2.26	9455	1053	89.98	10.02	2.27	2.11	0.07	0.000112
30	GA	14956	3.21	13451	1505	89.94	10.06	3.23	3.02	0.07	0.000147
31	OR	5946	1.28	5357	589	90.09	9.91	1.29	1.18	0.09	0.000099
32	WI	5908	1.27	5329	579	90.20	9.80	1.28	1.16	0.10	0.000120
33	TX	36398	7.81	32999	3399	90.66	9.34	7.93	6.82	0.15	0.001665
34	CT	7196	1.54	6537	659	90.84	9.16	1.57	1.32	0.17	0.000425
35	IL	18602	3.99	16890	1712	90.80	9.20	4.06	3.44	0.17	0.001054
36	SC	5580	1.20	5077	503	90.99	9.01	1.22	1.01	0.19	0.000399
37	CO	9735	2.09	8861	874	91.02	8.98	2.13	1.75	0.20	0.000760
38	AK	1251	0.27	1143	108	91.37	8.63	0.27	0.22	0.20	0.000100
39	MT	1394	0.30	1271	123	91.18	8.82	0.31	0.25	0.22	0.000132
40	KS	4186	0.90	3817	369	91.18	8.82	0.92	0.74	0.22	0.000396
41	NH	2230	0.48	2048	182	91.84	8.16	0.49	0.37	0.28	0.000336
42	VT	904	0.19	827	77	91.48	8.52	0.20	0.15	0.29	0.000145
43	MS	1224	0.26	1124	100	91.83	8.17	0.27	0.20	0.30	0.000210
44	WV	2410	0.52	2220	190	92.12	7.88	0.53	0.38	0.33	0.000495
45	WY	1128	0.24	1045	83	92.64	7.36	0.25	0.17	0.39	0.000312
46	DC	1425	0.31	1331	94	93.40	6.60	0.32	0.19	0.52	0.000676
47	IA	14	0.00	13	1	92.86	7.14	0.00	0.00	NaN	NaN

```
48  ID      12    0.00       11       1   91.67    8.33     0.00     0.00   NaN        NaN
49  ME       4    0.00        4       0  100.00    0.00     0.00     0.00   NaN        NaN
==============================================================================================
For 'AS' feature, sum of IVs = 0.0121: IV < 0.02 - no predictive power
==============================================================================================
```



Again, there are values which have a very low number of observations (e.g. `NE`), as well 50 different classes. These are therefore merged, according to `n_obs` and `WoE`, as

```
comb_dummy('AS',['FL', 'NV', 'HI', 'NE','AL'])              AS_CA 71369      AS_WA 10508
comb_dummy('AS',['LA', 'OK', 'NM'])                         AS_MD 10959      AS_FL+ 46465
comb_dummy('AS',['MO', 'UT', 'TN'])                         AS_MI 11542      AS_LA+ 12180
comb_dummy('AS',['AZ', 'AR', 'SD', 'RI'])                   AS_NC 12669      AS_MO+ 16908
comb_dummy('AS',['KY', 'MN', 'IN', 'MA', 'DE'])             AS_NJ 18039      AS_KY+ 31434
comb_dummy('AS',['GA', 'OR', 'WI'])                         AS_NY 40189      AS_GA+ 26810
comb_dummy('AS',['CT', 'IL'])                               AS_OH 15228      AS_CT+ 25798
comb_dummy('AS',['SC', 'CO', 'AK', 'MT', 'KS'])             AS_PA 16416      AS_SC+ 22146
comb_dummy('AS',['NH', 'VT', 'MS', 'WV'])                   AS_TX 36398      AS_NH+ 6768
comb_dummy('AS',['WY', 'DC', 'IA', 'ID', 'ME']);            AS_VA 14211      AS_WY+ 2583
```

where the resulting classes and `n_obs` are shown in the two right-hand columns. Arguably `AS_NH+` and `AS_WY+` could also be merged to increase the size of this class, but with $WoE = 0.28 - 0.33$, cf. ≥ 0.39, respectively, this is left as is.

2.2.7 Initial list status

This is the initial listing status of the loan.

```
  ILS   n_obs  %n_obs  n_good  n_bad  %good   %bad  %n_good  %n_bad   WoE        IV
0   f  302666   64.97  267251  35415  88.30  11.70    64.24   71.06 -0.10  0.006820
1   w  163173   35.03  148751  14422  91.16   8.84    35.76   28.94  0.21  0.014322
===============================================================================================
For 'ILS' feature, sum of IVs = 0.0211: 0.02 < IV < 0.1 - weak predictive power
===============================================================================================
```

With only two values, each with a large number of observations, this can be converted directly to dummy variables.

Now that the second phase of the pre-processing is complete, the fully processed data are saved (to `loan_data_2007_2014_2.csv`).

3 Machine Learning

3.1 Initial models and tests

The standard practice is to model the *probability of default* (PD) with the logistic regression classifier. Since, it is straightforward to run other common, but different, binary classifiers in tandem with this, I include these in the modelling. That is, the data are tested with:

1. *Logistic Regression* (LR)
2. *k-Nearest Neighbour* (kNN)
3. *Support Vector Classifier* (SVC)
4. *Decision Tree Classifier* (DTC)

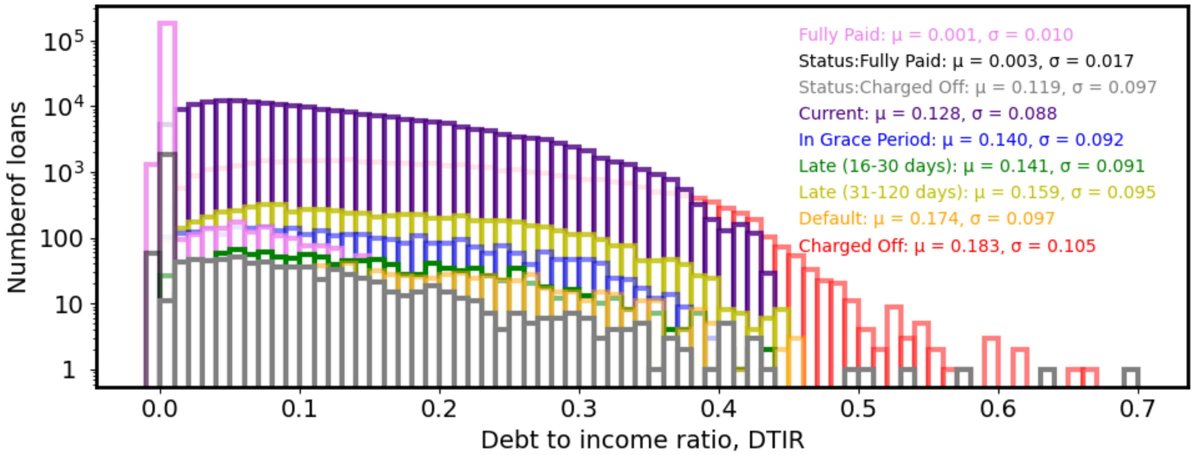
Each of which is described in further detail by Curran (2021).

The machine learning is performed in `ML.py`, where the imbalance in the data has to be addressed. Specifically, there are 49 782 bad loans compared to 465 839 - 49 837 = 416 057 good loans, and so from raw statistics alone we can ascertain a $100 \times 416\,057/465\,839 = 89.3\%$ probability of the loan being good, although this would have no predictive power. Therefore 49 837 of the good loan from the pool of 416 057 are randomly selected for the binary testing.

Training on 80% and testing on 20% of the sample, using (close to) the default standard parameters (`n_neighbors` = 10 and `max_depth` = 5), high scores are obtained, especially for the decision tree classifier.

```
For a 0.2 test fraction (79651 train & 19913 test) LR score = 92.418
For a 0.2 test fraction (79651 train & 19913 test) KNN score = 80.765
For a 0.2 test fraction (79651 train & 19913 test) SVC score = 93.851
For a 0.2 test fraction (79651 train & 19913 test) DTC score = 98.463
```

Such high scores may not be unexpected since the target was defined via the `loan_status`, i.e. `good = 1` where DTIR < 0.15 and `good = 0` where DTIR > 0.15 (Sect. 2.1.5).

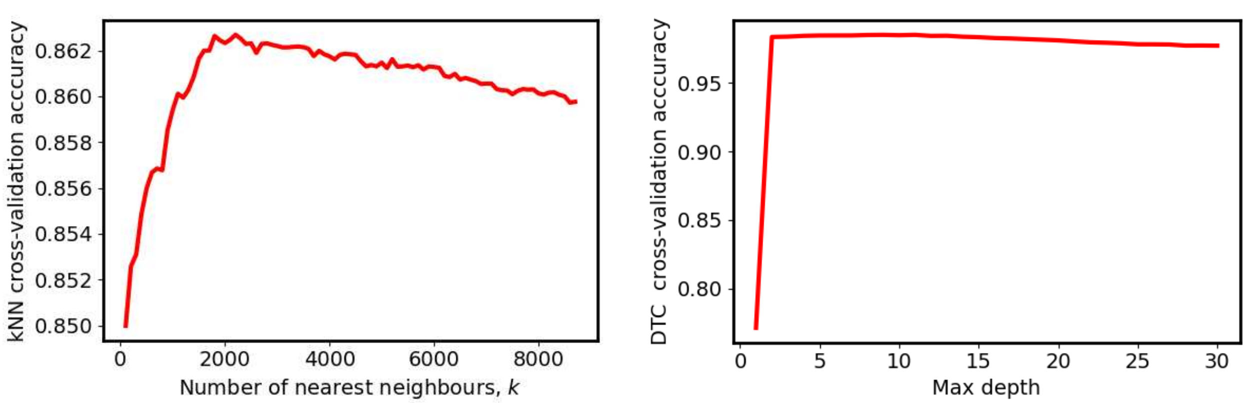


Using target_classes.py, the above plot shows the debt-to-income ratio distributions for each status. These overlap to such an extent that any prediction of the status based upon the DTIR alone would essentially be guesswork.

3.2 Model optimisation

Although the SVC scores relatively high, it is far from the highest and very CPU intensive for this size of dataset. As such, the effort required to optimise it is not justified, especially since the must faster DTC yields a score of 98%.

Using LR.py, for the LR classifier a grid search was very CPU intensive and failed to complete. Manual experimentation honed in on `C=10, solver='newton-cg'` as close to optimal.



Using kNN.py and DTC.py for the kNN and DT classifiers, the number of nearest neighbours and maximum depths were iterated, giving `n_neighbors` ≈ 2000 (a score of 86.2%) and `max_depth` = 10 (98.5%), respectively.

The array to the right shows the confusion matrix for a run of the DT classifier.

	Predicted training		Predicted validation	
	Good	**Bad**	**Good**	**Bad**
Actual good	39 148	136	9747	78
Actual bad	688	39 679	199	9889

The validation data yield 9747 true positives (good loans) and 9889 true negatives (bad loans), compared to 78 false positives and 199 false negatives. This gives a test score of (9747 + 9889)/(9747 + 9889 + 78 + 199) = 0.986.

3.3 Feature importance

In order of decreasing positive importance for the LR and DT classifiers:

```
LR score = 92.414
                      Feature    Importance
18              total_pymnt_inv  2.735509e-01
2               funded_amnt_inv  2.131122e-01
16                out_prncp_inv  1.798998e-01
15                    out_prncp  1.369901e-01
19              total_rec_prncp  1.268308e-01
22                   recoveries  1.016987e-01
20                total_rec_int  7.564751e-02
0                     loan_amnt  6.755471e-02
5                   installment  4.535285e-02
31                         LP_m  4.472009e-02
1                   funded_amnt  2.436630e-02
33                         debt  1.769972e-02
24              last_pymnt_amnt  1.458362e-02
23      collection_recovery_fee  1.275314e-02
21           total_rec_late_fee  1.230367e-02
32                        LCP_m  3.881935e-03
34                         DTIR  2.013785e-03
30                     issued_m  1.011914e-03
4                      int_rate  9.014325e-04
12                    revol_bal  3.013145e-04
3                          term  1.983654e-04
29                        ECL_m  1.757668e-04
14                    total_acc  1.556792e-04
10                     open_acc  1.556792e-04
74                        ILS_f  1.205258e-04
75                        ILS_w  1.205258e-04
28                         EM_L  1.155039e-04
56                        AS_NC  1.054601e-04
46           VS_Source Verified  7.532862e-05
72                       AS_NH+  6.528480e-05
25   collections_12_mths_ex_med  6.277385e-05
```

```
DTC score = 98.485
                      Feature  Importance
31                       LP_m    0.305927
33                       debt    0.242985
16              out_prncp_inv    0.079218
19            total_rec_prncp    0.030872
5                 installment    0.024627
24            last_pymnt_amnt    0.021162
15                  out_prncp    0.016005
21         total_rec_late_fee    0.014189
30                   issued_m    0.011912
34                       DTIR    0.006235
4                    int_rate    0.003073
3                        term    0.002850
9              inq_last_6mths    0.001361
20              total_rec_int    0.001361
6                  annual_inc    0.001238
18            total_pymnt_inv    0.000992
7                         dti    0.000859
13                 revol_util    0.000379
22                 recoveries    0.000331
14                  total_acc    0.000254
28                       EM_L    0.000171
17                total_pymnt    0.000141
8                 delinq_2yrs    0.000126
36                    grade_B    0.000118
12                  revol_bal    0.000118
2             funded_amnt_inv    0.000110
45            VS_Not Verified    0.000098
29                      ECL_m    0.000095
23    collection_recovery_fee    0.000093
42                HO_MORTGAGE    0.000078
1                 funded_amnt    0.000068
```

7	dti	5.775194e-05	10	open_acc	0.000063
39	grade_E	5.273003e-05	46	VS_Source Verified	0.000045
45	VS_Not Verified	5.273003e-05	56	AS_NC	0.000043
65	AS_LA+	4.519717e-05	63	AS_WA	0.000033
71	AS_SC+	3.766431e-05	52	P_credit_card+	0.000030
69	AS_GA+	3.013145e-05	72	AS_NH+	0.000030
51	P_home_improvement+	3.013145e-05	54	AS_MD	0.000025
55	AS_MI	2.762049e-05	65	AS_LA+	0.000025
53	AS_CA	2.008763e-05	0	loan_amnt	0.000020
40	grade_F	1.506572e-05	64	AS_FL+	0.000018
61	AS_TX	1.506572e-05	41	grade_G	0.000015
62	AS_VA	1.506572e-05	49	P_other+	0.000015
41	grade_G	1.506572e-05	48	P_small_business+	0.000015
70	AS_CT+	1.255477e-05	53	AS_CA	0.000015
73	AS_WY+	1.255477e-05	68	AS_KY+	0.000015
43	HO_RENT+	7.532862e-06	38	grade_D	0.000010
49	P_other+	5.021908e-06	50	P_debt_consolidation+	0.000008
8	delinq_2yrs	2.510954e-06	47	VS_Verified	0.000000
60	AS_PA	2.510954e-06	62	AS_VA	0.000000
54	AS_MD	2.510954e-06	74	ILS_f	0.000000
57	AS_NJ	0.000000e+00	73	AS_WY+	0.000000
26	policy_code	0.000000e+00	11	pub_rec	0.000000
42	HO_MORTGAGE	0.000000e+00	71	AS_SC+	0.000000
48	P_small_business+	-2.220446e-17	70	AS_CT+	0.000000
64	AS_FL+	-2.510954e-06	69	AS_GA+	0.000000
59	AS_OH	-2.510954e-06	25	collections_12_mths_ex_med	0.000000
9	inq_last_6mths	-5.021908e-06	67	AS_AZ+	0.000000
27	acc_now_delinq	-5.021908e-06	66	AS_MO+	0.000000
67	AS_AZ+	-7.532862e-06	26	policy_code	0.000000
37	grade_C	-1.004382e-05	27	acc_now_delinq	0.000000
68	AS_KY+	-1.255477e-05	32	LCP_m	0.000000
38	grade_D	-1.255477e-05	61	AS_TX	0.000000
50	P_debt_consolidation+	-1.757668e-05	44	HO_OWN+	0.000000
66	AS_MO+	-2.259859e-05	60	AS_PA	0.000000
58	AS_NY	-2.259859e-05	59	AS_OH	0.000000
11	pub_rec	-2.259859e-05	58	AS_NY	0.000000
52	P_credit_card+	-2.259859e-05	57	AS_NJ	0.000000
47	VS_Verified	-2.259859e-05	35	grade_A	0.000000
36	grade_B	-2.510954e-05	55	AS_MI	0.000000
13	revol_util	-2.762049e-05	37	grade_C	0.000000
63	AS_WA	-3.515336e-05	39	grade_E	0.000000
35	grade_A	-4.017526e-05	40	grade_F	0.000000
6	annual_inc	-4.519717e-05	51	P_home_improvement+	0.000000
44	HO_OWN+	-1.129929e-04	43	HO_RENT+	0.000000
17	total_pymnt	-6.528480e-04	75	ILS_w	0.000000

Eliminating the least important features for the DT classifier (ML_feat.py), the retention of just the top two features (table to the right) – months since last payment (LP_m) and outstanding debt (loan_amnt - total_rec_prncp)[a] is sufficient to achieve 98% accuracy.

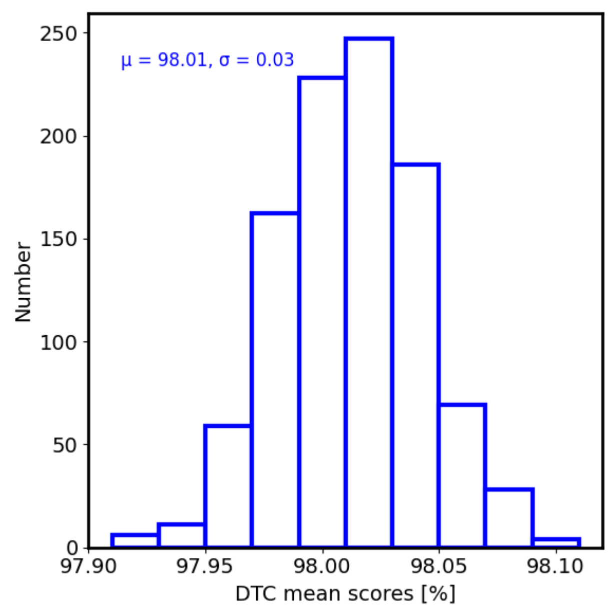
[a]The loan amount minus the principal received to date.

No. of top features	Last feature used	Feature importance	Score [%]
15	annual_inc	> 0.001	98.5
9	issued_m	> 0.01	98.6
6	last_pymnt_amnt	> 0.02	98.3
4	total_rec_prncp	> 0.03	98.1
2	debt	> 0.2	98.0
1	LP_m	–	77
1	debt	–	73

Again, this may be expected since the target value is defined by the mean debt feature normalised by the income. Thus, the model does have some embedded prior knowledge, although, as noted in Sect. 3.1, the spread of debt-to-income ratios for each loan status overlap so much that any direct prediction would not be reliable.

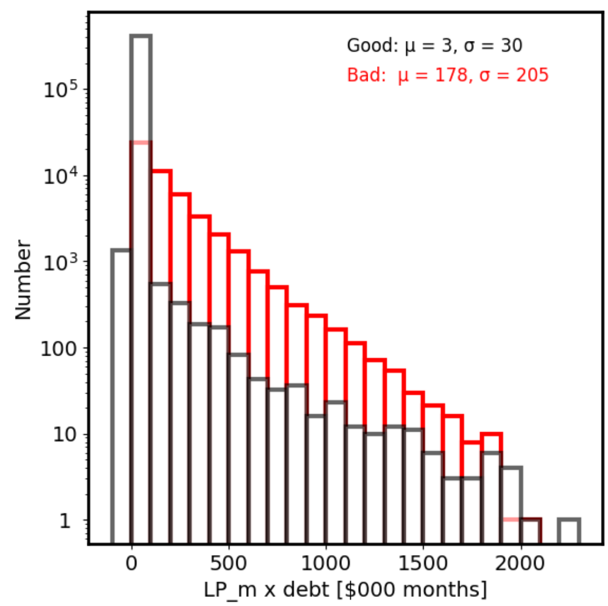
Note that, alternatively, testing the DT classifier with *all* features but LP_m and debt still gives a score 93.2%

It is thus apparent, that with just the *months since last payment*, *loan amount* and *principal received to date*, much of the above processing, including the coarse classing, is unnecessary (at least in this case). This may be evident via the low information values for most of the cetegorical variables (Sect. 2.2.)
In order to check that the high scores above are not a fluke, although the test sample is relatively large (19 913), 1000 trials of the DTC (LP_m and debt only) model were ran, randomising the sample of good =1 from the pool of 416 057 good loans (ML-loop_feat.py) each time.



From the resulting distribution of scores, shown by the histogram, it is clear that the score is in fact very stable, as would be expected from a random selection of nearly 20 000.

Given that the DT classifier can predict whether loan is good or bad with $\geq 73\%$ accuracy using either `LP_m` or `debt` alone, reaching 98% when both are used, it might be possible that a combination of these features shows a clear distinction between the good and bad loans.
Plotting the products (`2-feat_histo.py`), it is seen that the distributions are far from normal preventing us from performing a t-test. However, it is clear that the populations mostly overlap, with a large spread in the values.
Thus, it appears as though the machine learning is doing something more complex than a straightforward combination of these two features.



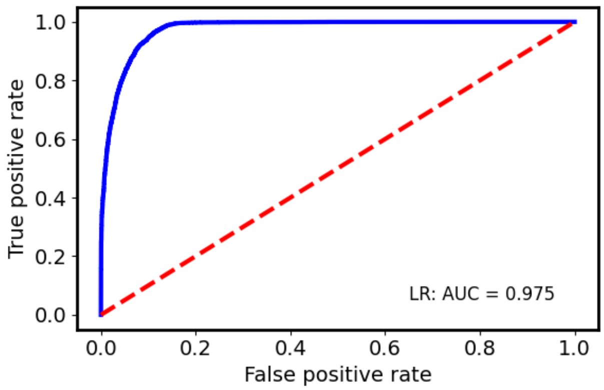
4 Results

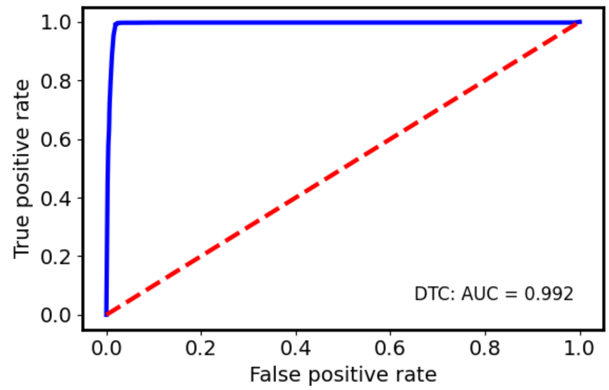
4.1 ROC curve

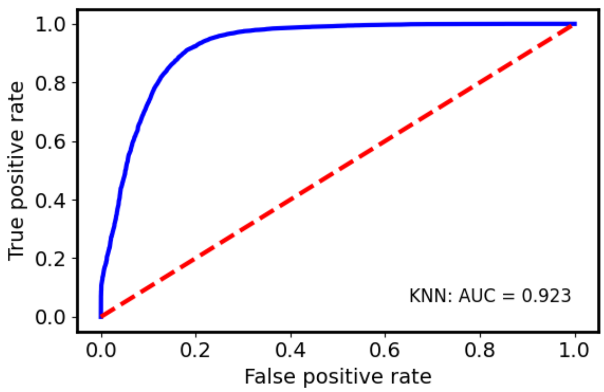
The *receiver operating characteristic* (ROC) is a plot of the *true positive rate* versus the *false positive rate*, obtained from the confusion matrix at a given classification threshold (e.g. $> 0.5 \Rightarrow$ `good` =1, $< 0.5 \Rightarrow$ `good` =0).

The area under area under the ROC curve (AUC) provides a measure of the effectiveness of the classification. The scores are grouped into categories in the table to the right. For example, predicting purely by chance gives the AUC = 0.5, shown by the red broken lines in the following plots.

Area under ROC curve	**Model Interpretation**
0.5 – 0.6	No discrimination
0.6 – 0.7	Poor classifier
0.7 – 0.8	Fair classifier
0.8 – 0.9	Good classifier
0.9 – 1	Excellent classifier







The DT classifier gives an AUC = 0.994, scoring much higher the 0.5 expected from chance and significantly higher than Udemy's Credit Risk Modelling in Python AOC of 0.702. *"In credit risk, an AUC of 0.75 or higher is the industry-accepted standard and prerequisite to model acceptance"* (from Credit Scoring Series Part Five).

4.2 Gini coefficient

The Gini coefficient measures the inequality between the `good = 1` and `good = 0` borrowers. This is obtained from the AUC, via

$$\text{Gini} = (2 \times \text{AUC}) - 1,$$

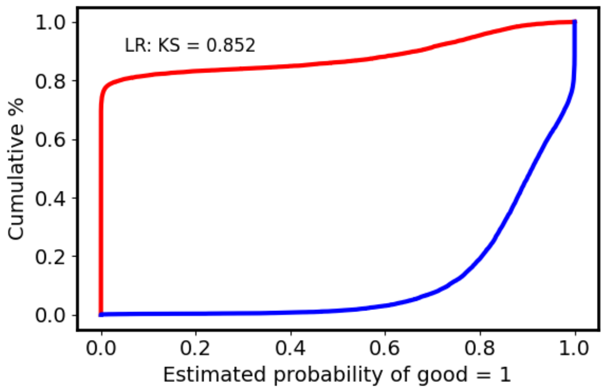
so that the higher the Gini coefficient the better the model in distinguishing the two classes.

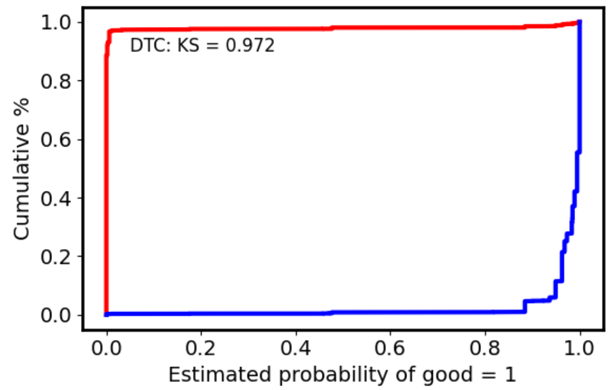
The above AUCs give Gini = 95% for LR, 98% for DTC and 85% for kNN, compared to 40%, from the same data, by Udemy and 71% by Credit Risk Modelling (Part II).

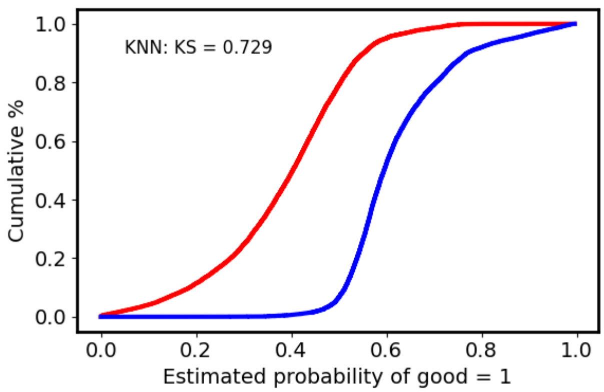
4.3 Kolmogorov-Smirnov score

The Kolmogorov-Smirnov (KS) test compares the distribution of a borrower's credit score with the reference distribution. It uses the maximum difference between the cumulative distribution functions to determine whether the two distributions are significantly different from each other.

We show the KS scores below for the LR and DT classifiers, where the blue trace represents the `good = 1` borrowers and the red trace the `good = 0` borrowers.







The KS scores of 0.73 – 0.71 are high, indicating that the models have excellent predictive power. Note that both Udemy and Credit Risk Modelling (Part II) obtain a score of just 0.30.

4.4 Using the Udemy Target Classification

Given the results are much superior to those of Udemy, in order to check that these are not due to the definition of the target (Sect. 2.1.5), we repeat the analysis using the Udemy classification.

Proceeding with `pre-process_Udemy_1.py`, the two classification schemes are shown below.

```
====== my_good = 1 ======
['Fully Paid' 'Current'
'In Grace Period' 'Late (16-30 days)'
'Does not meet the credit policy. Status:Fully Paid'
'Does not meet the credit policy. Status:Charged Off']
====== my_good = 0 ======
['Charged Off' 'Default' 'Late (31-120 days)']

Giving 416002 good loans (good = 1)
 and 49837 bad loans (good = 0)

mean           0.893017
std            0.309092
min            0.000000
max            1.000000
```

```
====== Udemy good = 1 ======
['Fully Paid' 'Current'
'In Grace Period' 'Late (16-30 days)'
'Does not meet the credit policy. Status:Fully Paid']
====== Udemy good = 0 ======
['Charged Off' 'Default' 'Late (31-120 days)'
 'Does not meet the credit policy. Status:Charged Off']

Giving 415256 good loans (good = 1)
 and 50583 bad loans (good = 0)

 mean           0.891415
 std            0.311118
 min            0.000000
 max            1.000000
```

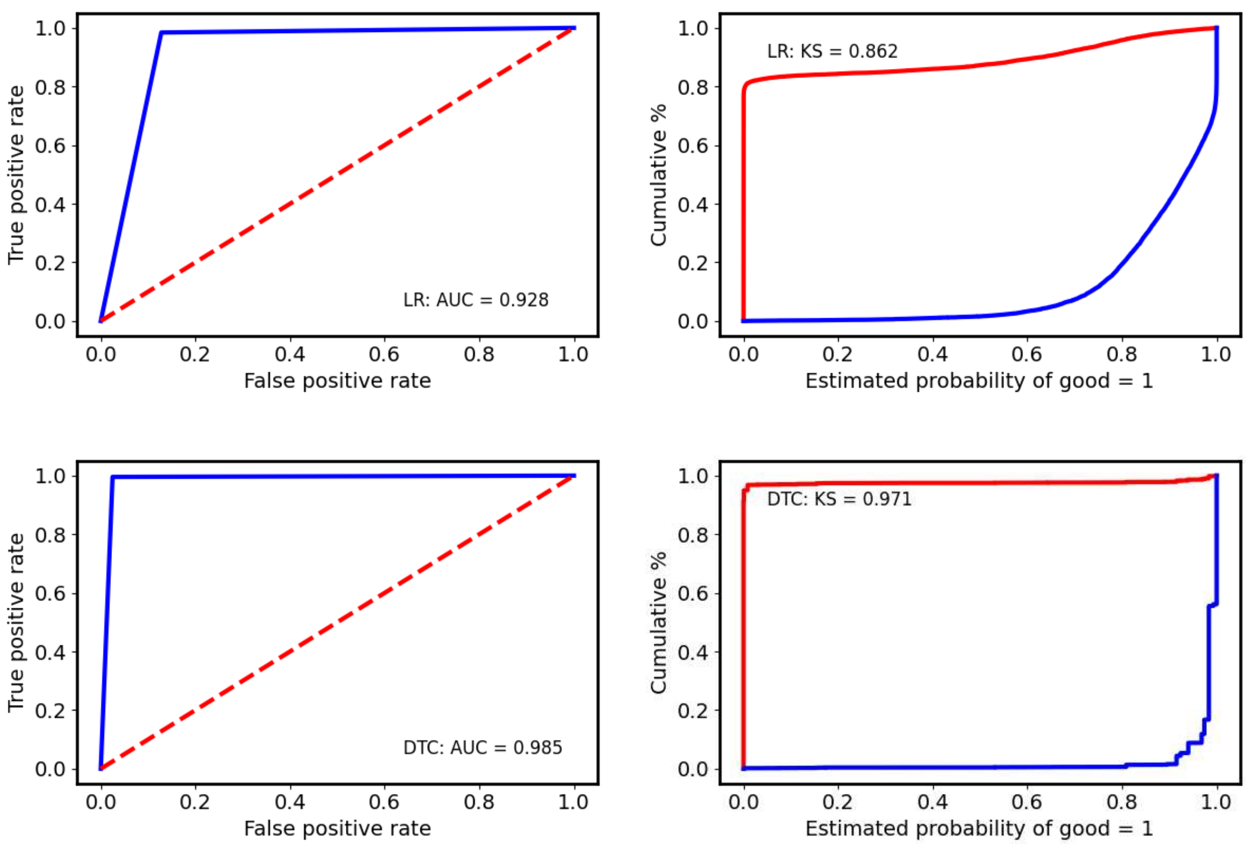
These are similar, with only `Does not meet the credit policy. Status:Charged Off` being classed differently.

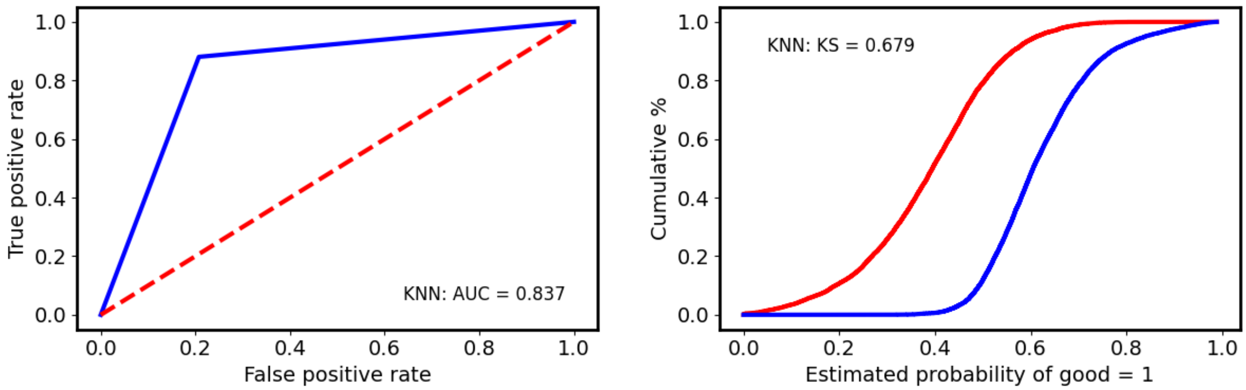
The previous steps (Sects. 2.1.2 – 2.2.7) are repeated for the Udemy classification, with the coarse classing done in `pre-process_Udemy_2.py` and the machine learning in `ML_Udemy.py`, where a randomly selected sample of 50 583 `good = 1` loans is used to match the number of `good = 0` loans.

A typical run of the various classifiers gives

```
For a 0.2 test fraction (80932 train & 20234 test) LR score = 92.762
For a 0.2 test fraction (80932 train & 20234 test) KNN score = 83.966
For a 0.2 test fraction (80932 train & 20234 test) DTC score = 98.563
```

which are very similar scores to those above. Therefore, the slightly different classification of loan status is not responsible for the high scores.





4.5 *IVs* of the Most Important Features

It has been shown above that retaining the continuous features results in a much superior predictive model, with a Gini coefficient of 98% (cf. 40% with fine classing) and a KS score of 0.97 (cf. 0.30).

Furthermore, at least for these data, the categorical features make a relatively small contribution with the decision tree classifier, which still attains accuracies of 98% from only two features – the months since the last payment (`LP_m`) and outstanding debt (`debt`).

```
====================== Months since last payment (LP_m) ==========================
         LP_m   n_obs  %n_obs  n_good  n_bad   %good   %bad  %n_good  %n_bad   WoE        IV
0    0.000000  179600   38.55  178818    782   99.56   0.44    42.98    1.57  3.31  1.370671
1    1.018501   61998   13.31   61147    851   98.63   1.37    14.70    1.71  2.15  0.279285
2    2.004148    9317    2.00    7411   1906   79.54  20.46     1.78    3.82 -0.76  0.015504
3    3.022649   11248    2.41    8975   2273   79.79  20.21     2.16    4.56 -0.75  0.018000
...
95  94.983470       7    0.00       7      0  100.00   0.00     0.00    0.00   NaN       NaN
96  96.001971       9    0.00       9      0  100.00   0.00     0.00    0.00   NaN       NaN
97  97.020473       2    0.00       2      0  100.00   0.00     0.00    0.00   NaN       NaN
===============================================================================================
For 'LP_m' feature, sum of IVs = 2.1116: IV >  0.5 - something fishy going on
===============================================================================================

====================== Outstanding debt in $000 (debt_k) =========================
     debt_k   n_obs  %n_obs  n_good  n_bad   %good    %bad  %n_good  %n_bad   WoE        IV
0      -0.6       1    0.00       1      0  100.00    0.00     0.00    0.00   NaN       NaN
1       0.0  185020   39.72  184999     21   99.99    0.01    44.47    0.04  7.01  3.114543
2       0.1     387    0.08     343     44   88.63   11.37     0.08    0.09 -0.12  0.000012
3       0.2     713    0.15     666     47   93.41    6.59     0.16    0.09  0.58  0.000406
...
348    34.8       1    0.00       0      1    0.00  100.00     0.00    0.00   NaN       NaN
349    34.9       1    0.00       0      1    0.00  100.00     0.00    0.00   NaN       NaN
```

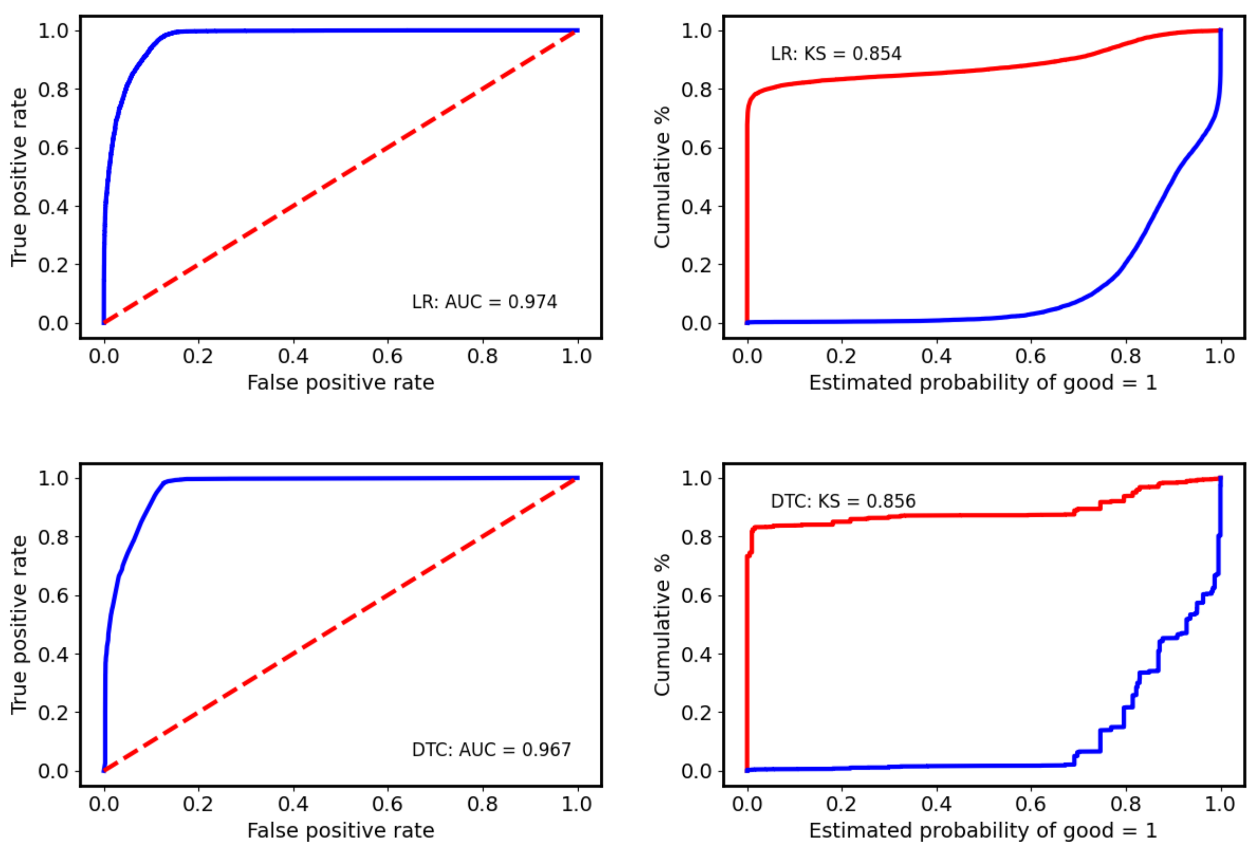
```
350    35.0       2    0.00       0      2    0.00  100.00     0.00    0.00   NaN       NaN
==============================================================================================
For 'debt_k' feature, sum of IVs = 3.4508: IV >  0.5 - something fishy going on
==============================================================================================
```

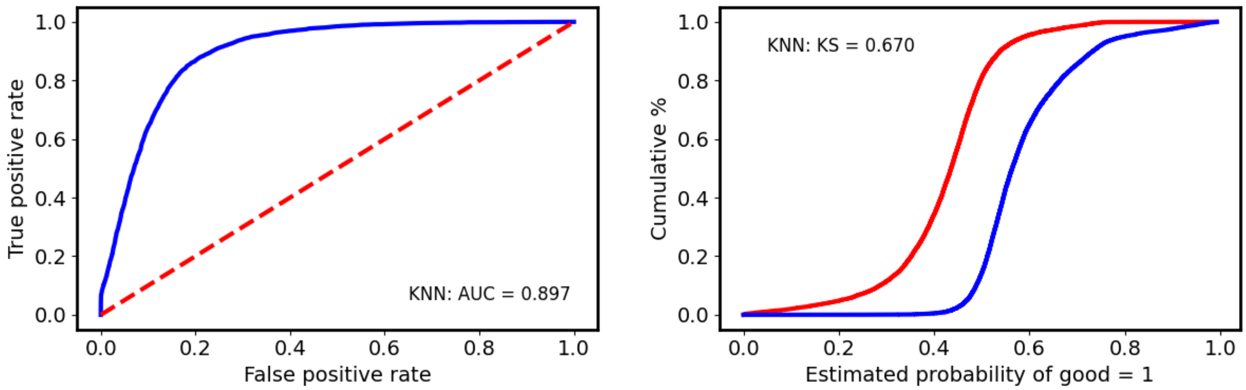
Looking at the information values, both are high, $IV \gg 0.5$, which suggests leakage. That is, they are acting as a proxy for the prediction, although, as seen from above, the relationship is not simple.

As mentioned in Sect. 3.3, however, the DT classifier maintains a 93% accuracy when all the features *except* these two are used. This is most likely due to the richness of the dataset which still comprises 74 features. In order to test if the above is the result of leakage, in `ML_all-others.py` we remove these features as well as the debt-to-income ratio and the annual income:

```
del df['LP_m']; del df['debt']; del df['DTIR']; del df['annual_inc']
```

The cross-validation score remains high, at 93%, and the Gini ceofficient is 0.94 with a KS score ≥ 0.85 for both the LR and DT classifiers.





That is, high scores are still attained without the features used to define the target, suggesting that the results are not dominated by leaskage.